

Joint Angle Estimation Using Soft Wearable Sensor Measurement

Zenan Zhu¹, Janelle P. Clark², Lina Sanchez-Botero³, Anjali Agrawala³, Rebecca Kramer-Bottiglio³,
Pei-Chun Kao², Holly Yanco², Yan Gu¹

I. MOTIVATION

Exoskeletons have the potential to enhance the endurance of able-bodied individuals engaged in prolonged and physically demanding tasks in various settings [1]–[3]. However, the challenges associated with the use of exoskeletons by able-bodied wearers include the lack of accommodation for fatigue and inadequate sensing capabilities, leading to excessively high levels of continuous actuation, consuming more power than necessary, and reducing human capability with continued use. Recently, the advancement of soft sensors has provided the possibility of measuring human movement more comfortably [4]. In this study, we propose an online auto-calibration algorithm to accurately map the raw data obtained from soft sensors to the wearer’s leg joint angles.

II. METHODOLOGY

Extended Kalman filtering (EKF) is used in this study because of the model’s nonlinearity. The proposed algorithm intends to estimate the wearer’s left knee joint angle accurately by using the raw fabric sensor reading as one input. We assume a linear relationship between the raw soft sensor reading and the joint angle as $\theta := k\alpha + b$, where θ is the left knee joint angle, k is the slope, and b is the angle offset. The state variables are $\mathbf{X} := [\mathbf{p}, \mathbf{v}, \mathbf{R}, \theta, k, b]^T$, where \mathbf{p} , \mathbf{v} , and \mathbf{R} are the position, velocity, and orientation of the inertial measurement unit (IMU) at the left ankle exoskeleton, expressed in the world frame, respectively. The non-slip condition between the subject’s right foot and the ground is utilized as one measurement model [5] [6], which is given as:

$$\dot{\mathbf{d}} = \mathbf{0} = \mathbf{v} + \mathbf{R}\mathbf{J}(\theta)\dot{\theta} + \mathbf{R}(\boldsymbol{\omega}) \times \mathbf{h}(\theta), \quad (1)$$

where \mathbf{d} is the right foot position, $\boldsymbol{\omega}$ is the angular velocity obtained from the IMU, $\mathbf{h}(\theta)$ is the forward kinematics from the IMU to the right foot that contains the joint angle state, and $\mathbf{J}(\theta)$ is the Jacobian matrix of $\mathbf{h}(\theta)$.

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¹Z. Zhu is with the School of Mechanical Engineering, Purdue University, West Lafayette, IN 47907, USA zhu_1134@purdue.edu.

¹Y. Gu is with the School of Mechanical Engineering, Purdue University, West Lafayette, IN 47907, USA.

²J. Clark and H. Yanco are with the Richard A. Miner School of Computer & Information Sciences, University of Massachusetts Lowell, Lowell, MA 01854, USA.

²P. Kao is with the Department of Physical Therapy and Kinesiology, University of Massachusetts Lowell, Lowell, MA 01854, USA.

³L. Sanchez-Botero, A. Agrawala, and R. Kramer-Bottiglio are with the Department of Mechanical Engineering & Materials Science at Yale University, New Haven, CT 06520, USA.

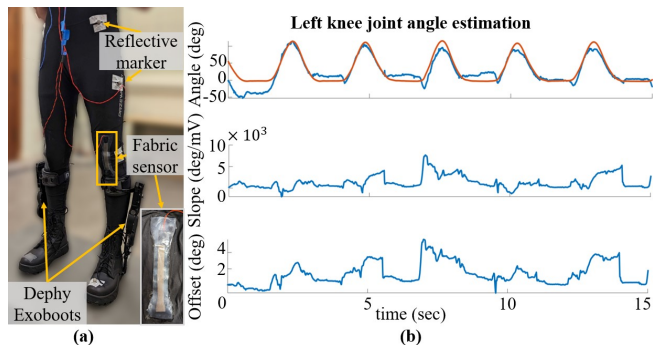


Fig. 1. (a) Experimental setup used to collect the ground truth of the estimated state variables and the sensor data required for the proposed filter. (b) Estimation results of joint angle, angle slope, and angle offset of the left knee joint.

III. PRELIMINARY RESULTS AND DISCUSSION

A new fabric sensor developed in the Laboratory Lab at Yale University [7] has been utilized in this work. The fabric sensor was attached over the left knee joint along the sagittal plane, and a motion capture system and reflective markers were used to obtain the joint angle data as ground truth (as shown in Fig. 1(a)). The subject was asked to perform the squatting motions for one minute while wearing a pair of ankle exoskeletons.

Fig. 1(b) shows that the estimated joint angle converges to the true value even with 50 degrees initial joint angle error. The initial validation confirms the effectiveness of the proposed approach. Our future work aims to simultaneously estimate both hip and knee joint angles for both legs.

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